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Transformer Fault Diagnosis Method Based on Device Portrait and Improved SqueezeNet

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Abstract
To make full use of the multi-source state information of the fault transformers and improve the accuracy of fault identification, the equipment portrait technology is introduced to construct the similarity matrix from original data through the Mahalanobis distance to mine the implicit relationship between the fault features, and the genetic algorithm is used to optimize the spectral clustering center to construct the accurate portrait of transformers. Then, taking advantage of the lightweight network to improve SqueezeNet, constructing a new SqueezeNet-GRU network. The characteristic parameters after portrait are used as network input, and the optimal parameters are obtained through multiple trainings to form the transformer fault diagnostic model. Finally, the accuracy, recall, and comprehensive value F1 are selected as the evaluation indexes of the diagnostic model. The experimental results show that the diagnostic accuracy of the model in each fault type is improved compared with GRU and CNN-GRU, and the overall diagnostic accuracy is improved by 6% and 5% respectively.

Keywords: *Equipment portrait, SqueezeNet, Gated Recurrent Unit, fault diagnosis*

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I. INTRODUCTION

Transformers are the core equipment of the power system and play a vital role in power generation, voltage conversion, and power distribution. The distribution transformer refers to the transformer that operates in distribution network with a voltage class of 10-35 kV and a capacity of 6300 kVA and below that directly supplies power to end-users. It carries important tasks such as power transmission and power distribution. With the gradual increase in the scale of the power grid, the demand for distribution transformers continues to increase, and the probability of occurring faults has also increased [1]. Once the distribution transformer fails, it will inevitably cause safety accidents such as local outages and even fires, which will bring huge losses to the user's production and life, and also seriously affect the reliable operation of the entire distribution system [2]. Therefore, making an accurate and rapid assessment of the health of the transformer is meaningful to the stable operation and healthy development of the power grid [3].

At present, the transformer fault diagnosis methods mainly include Dissolved Gas Analysis (DGA), which discriminates the fault type according to the characteristic gas composition and content produced in the insulating oil. It is a simple and effective analysis method [4]. However, the traditional DGA has some problems, such as incomplete encoding and too absolute boundary, which increases the error rate of fault diagnosis [5]. With the rapid development of artificial intelligence, machine learning method has been widely used in the field of transformer fault diagnosis. According to the characteristics of transformer fault data, Zhao et al. [6] improved autoencoder and standardized the input of each layer of the autoencoder network, which greatly shortens the model training time. However, this method cannot fully extract the fault information characteristics of transformers, which affects the diagnostic accuracy to a certain extent. Wei [7] added a dynamic parameter in the process of neural network weight correction to overcome the local minimum problem of backpropagation neural network, reduced the number of hidden layer neurons, and then verified the network performance by stepwise regression method, but the network structure is complex, which brings inconvenience to the diagnostic

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process [8]. Zhao [9] proposed a transformer fault diagnostic model based on residual backpropagation neural network. Stacking multiple residual network modules to form a deep neural network, and the output of this layer and the input of the previous layer are used as the output of the residual block. The input information does not have to be transmitted layer by layer, so it is better to extract the transformer fault characteristic information. However, because the model uses multiple residual blocks, there are many disadvantages, such as a large number of hidden layer neurons and complex calculations. Tu et al. [10] used genetic algorithm to optimize the penalty factor and kernel parameters of the support vector machine and used 20 characteristic data as model input, but the diagnostic accuracy of the model is still insufficient under small sample data. Hu et al. [11] proposed a transformer fault diagnostic method based on confidence rule bases. Thus, the fault gas type is reduced and the model parameters are simplified, and then aiming to parameter sensitivity, using the crowd search algorithm to optimize the parameter, so the transformer diagnostic accuracy is improved. However, the information transformation method and weight calculation process are complex, which is easy to cause reasoning errors.

In response to the above problems, this paper proposes a transformer fault diagnostic model based on multi-dimensional device portrait and improved SqueezeNet model. On the one hand, introducing the genetic algorithm to spectral clustering can avoid the sensitive problem of the initial clustering center, find rapidly the optimal clustering center, and achieve accurate transformer portraits. On the other hand, it integrates and improves the SqueezeNet model and Gated Recurrent Unit. Guaranteeing the extraction of the time and space features of the transformer data, which makes the model have a higher detection accuracy.

II. TRANSFORMER PORTRAIT METHOD BASED ON IMPROVED SPECTRAL CLUSTERING

2.1 Data preprocessing

Due to the influence of rated power, voltage classes, model, manufacturer, and load, the content of dissolved gas in transformer insulating oil has a more complicated relationship with the type and severity of the fault [12]. In order to construct comprehensively the transformer portrait, this paper conducts a comprehensive state analysis of the transformer through attribute information and online monitoring data. The dimensions of the original data of each indicator are different and the data disparity is large, so the min-max standardization is applied to preprocess the original data to make the indicators comparable [14].

The attribute information of the transformer refers to the inherent information of the equipment that reflects the performance of the transformer, such as rated power, voltage classes, service life, model, and other information. Online monitoring data refers to the measurement data during transformer operation, such as metal element content in insulating oil, dissolved gas concentration, oil temperature, and other information. X_1 and X_{s1} represent the fault information before and after standardization respectively, and the standardization formula is given by:

$$X_{s1} = \frac{X_1 - X_{1\min}}{X_{1\max} - X_{1\min}} \tag{1}$$

2.2 Transformer portrait based on genetic optimization

The essence of the transformer portrait is to obtain effective historical data and online monitoring information of the transformer, perform cluster analysis through the collected status data. Spectral clustering has a wide range of applications in many clustering methods due to its rigorous mathematical theory. It can avoid the over-fitting problem caused by the high dimensionality of the input data to a certain extent [13]. However, the initial center of k-means algorithm in traditional spectral clustering is random, so we cannot obtain a good clustering effect. In order to overcome the sensitivity problem of the initial clustering center in spectral clustering, this section uses genetic algorithm to optimize the standardized Laplacian matrix to obtain the transformer samples with the greatest adaptability and constructs a multi-dimensional transformer health status portrait.

The steps of using improved spectral clustering to construct transformer portrait are as follows:

Step 1: Construct the similarity matrix **W**. This paper uses the Mahalanobis distance [15] to calculate the similarity matrix of the sample space. The matrix can be represented by an undirected graph, where the element w_{ij} represents the weight of the nodes v_i and v_j, and the calculation expression of W is as follows.

$$\mathbf{W}(v_i, v_j) = \sqrt{(v_i - v_j)^T C^{-1} (v_i - v_j)} \quad , i \neq j \tag{2}$$

In the formula, symbol **C** is the covariance matrix of multi-dimensional random variable.

Step 2: Build the diagram structure. Taking the eigenvector of the transformer samples as the node in the graph, using the similarity calculated in step 1 to judge the adjacency relationship between the two nodes, and the edge set is built to form the graph structure.

Step 3: Calculate the Laplace matrix $\mathbf{L} = \mathbf{D} - \mathbf{W}$, where **D** is the degree matrix.

Step 4: Standardize the Laplace matrix to obtain k_1 eigenvectors corresponding to eigenvalue $(b_1 b_2 b_3 \dots b_{k_1})$. Standardizing the matrix composed of eigenvectors according to rows to form the eigenmatrix $\mathbf{R}_{\mathbf{n}}^{\mathbf{k_1}}$.

Step 5: Initialize the population. Each vector of Matrix $\mathbf{R}_{\mathbf{n}}^{\mathbf{k_1}}$ is regarded as a sample to generate the initial population. Then setting the population size, crossover probability, mutation probability, and iteration times.

Step 6: Define the fitness function. The fitness function affects the convergence speed of genetic algorithm. In this paper, constructing the fitness function g to define the fitness of nodes.

$$g = \frac{a}{1 + S} \tag{3}$$

Where a is a constant and S is the sum of squared errors in the sample space.

Step 7: Select individuals with high fitness. In this paper, roulette is selected as the selection method, and the individual with the highest fitness is collected in each generation of the population, and the probability of an individual being selected is proportional to its fitness [16].

Step 8: Perform crossover and mutation operations.

Step 9: Iteration. Repeating steps 6 to 8 until the number of iterations is met.

Step 10: Select the globally optimal cluster center to obtain the transformer portrait.

III. SQUEEZENET INTRODUCTION AND SQUEEZENET-GRU MODEL DESIGN

3.1 SqueezeNet model

Since AlexNet [17] in 2012, convolutional neural networks have been widely studied and applied to the fields of image classification, GraphCut, and target image detection. With the continuous improvement of network performance, AlexNet has been unable to meet the application need of researchers. Many researchers have researched and developed CNN networks with better performance. Due to the network complexity of the neural network, in order to get better processing performance, the number of layers included in the network continues to increase, from 7 layers of AlexNet to 16 layers of VGGNet [18], and 22 layers of GoogleNet [19] and so on. Some networks have even more than a thousand layers. Although the classification effect of these neural networks has been greatly improved, the direct result that follows is the processing efficiency problem of neural networks. In order to solve the efficiency-related problem of CNN, and to have a higher universality on the mobile terminal, lightweight model design came into being. SqueezeNet [20] is a typical lightweight network model. The main thinking used in the design process is: because of the actual characteristics of the convolution method, a network calculation method with better effectiveness is proposed. On the basis of the significant reduction of the included parameters, it still has a relatively powerful comprehensive performance. Figure 1 is an intuitive internal structure diagram.

As shown in Figure 1, there are 3 pooling layers in the classic structure of SqueezeNet, including pooling layer A, pooling layer B, and pooling layer C. Each time through a data pooling layer, the size of the data is converted to half of the original, so that the scale of calculations that the network needs to carry out is significantly reduced. The 1×1 convolution kernel is used in the convolutional layer 2, and the input and output channels are set to be 512 and 1000 respectively. The average pooling process is carried out for the whole, and the softmax layer is used to solve the probability corresponding to the classification process. The global average pooling refers to averaging the feature map of each output channel so that the output feature dimension of this layer is equal to the number of output channels of this layer.

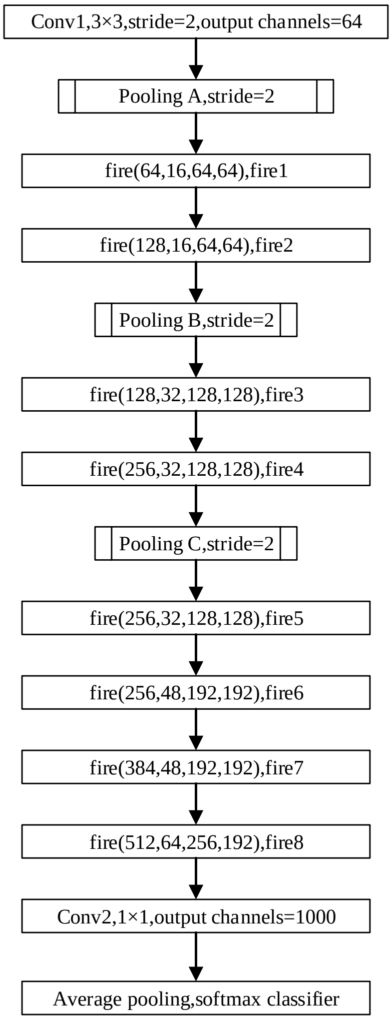

Figure 1: SqueezeNet structure

In Figure 2, the squeeze layer is a convolutional layer with a convolution kernel of 1×1, which changes the input channel from M to N, usually N smaller than M. The squeeze layer is mainly used to compress the input channel to reduce the amount of data calculation of network as much as possible. The convolution kernel used of the convolution layer contained in the expand layer is divided into 1×1 and 3×3. The 1×1 convolution kernel and 3×3 convolution kernel respectively expand the input channel from N to E_1 and E_2. Finally, splicing the feature map obtained from 1×1 and 3×3 to get the feature map of the output channel $(E_1 + E_2)$.

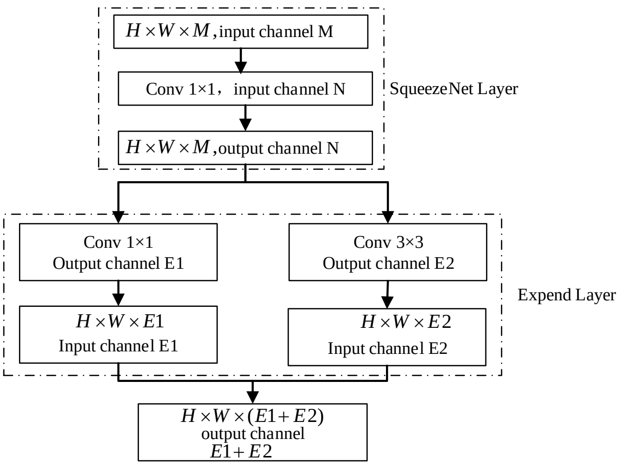

Figure 2: Fire module structure

3.2 SqueezeNet-GRU model design

For the detection of transformer fault on the power distribution Internet of Things, the SqueezeNet mentioned in the previous section is adaptively improved. The traditional convolutional neural network series methods are mostly used to extract the spatial features of the image. Transformer fault data is closely related to power grid topology structure, and transformer fault data has intense time series characteristics. In order to maintain the time characteristics in the data, a special Recurrent Neural Network is considered in this paper.

Long Short-Term Memory (LSTM) [21], as the name of the network, can extract data time-series features. The training of LSTM is relatively slow. The Gated Recurrent Unit (GRU) [22] is slightly modified on its basis, so that the detection speed has been improved, and the accuracy has not changed much, which indicates the GRU model is more popular than LSTM model. In this paper, the lightweight network is improved, and the SqueezeNet and GRU network are merged to construct the SqueezeNet-GRU model. This model greatly reduces the number of network parameters, shortens the training time, and improves the stability and accuracy of detection of network. Figure 3 shows the structure of the SqueezeNet-GRU model.

Among them, fire is the fire model structure, ①, ②, and ③ are convolution processing links with the same structure. FC is the fully connected layer, and softmax is the classifier. After convolution layer 1 in Figure 3, a preliminary convolution feature map is obtained, and then through maximum pooling layer 1, a new convolution feature map is output. The feature map is obtained through the processing of ①, and the processing processes of ② and ③ are similar to that of ①. The GRU network unit in Figure 3 reshapes the input feature map to obtain a new feature vector, Afterward, inputting these feature vectors into two GRU networks in turn, and performing dimensionality reduction in the GRU. Finally, splicing input to FC and softmax layer, and then getting the output result.

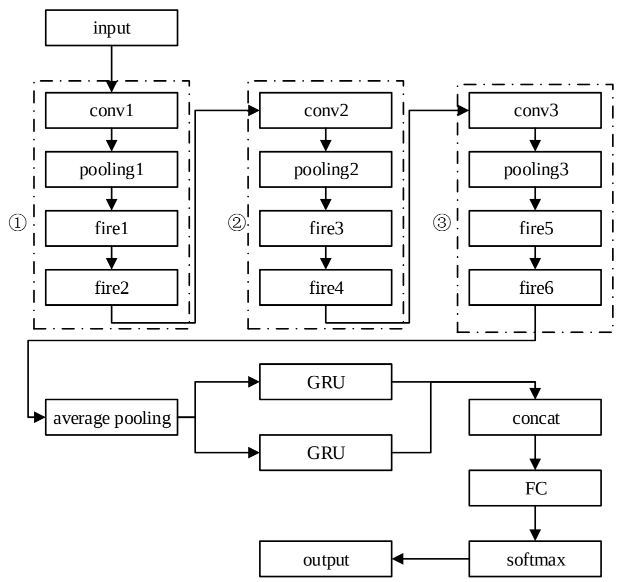

Figure 3: Structure of SqueezeNet-GRU model

IV. DIAGNOSIS MODEL BASED ON EQUIPMENT PORTRAIT AND SQUEEZENET-GRU

4.1 Transformer fault diagnosis model based on equipment portrait and SqueezeNet-GRU

Performing training based on the SqueezeNet-GRU network structure in the previous section, then inputting the portrait results into the trained neural network to conduct transformer fault diagnosis. Diagnosis steps based on the equipment portrait and SqueezeNet-GRU network are shown in Figure 4.

1) Data preprocessing. preprocessing the historical data and online monitoring data. N measurement vectors X after specific processing compose matrix **Z** of n×m and are normalized.

2) Transformer portrait. For the preprocessed data, calculating the similarity matrix by the Mahalanobis distance method to construct graph structure, then calculating the Laplacian matrix, obtaining the cluster center by the genetically optimized spectral clustering algorithm, and iterating until the maximum number of cycles is satisfied. Finally, the optimal cluster center is regarded as the result of the portrait.

3) Input the feature data after the portrait into the network model shown in Figure 4, and respectively go through the convolutional layer, the maximum pooling layer, and the fire structure to achieve feature extraction and data dimensionality reduction.

4）After repeating the previous step many times, bring the obtained results into the GRU unit so that it can enter the update door and reset door. The update door defines the impact level of the information of the previous time on the subsequent time. When its corresponding value is large, indicating the information of the previous time will have a significant impact on the subsequent time. The definition of reset gate is mainly to weaken the influence of the information of the previous time. Therefore, when the corresponding value is small, it can have a significant weakening effect.

5) Finally, transmitting the results to the FC layer. The softmax classifier is used to complete the fault diagnosis process, then outputting the results.

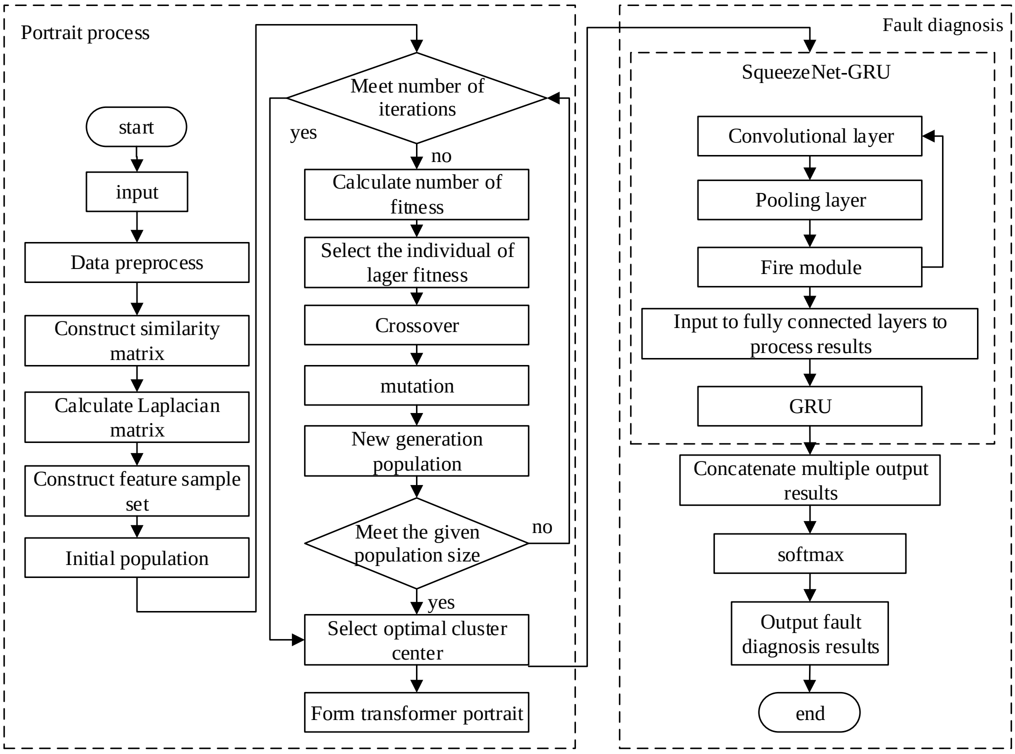

Figure 4: Transformer fault diagnosis process based on equipment portrait and SqueezeNet-GRU

4.2 Model detection performance evaluation index

In the performance evaluation system of neural network model, the model evaluation indexes generally include accuracy, precision, and recall. These indicators involve a basic concept of chaotic matrix [23], as shown in Figure 5, in order to verify the effectiveness and feasibility of the diagnostic method proposed in this paper, four evaluation indexes are introduced: accuracy, precision, recall, and comprehensive value F1.

Actual fault status

Diagnostic fault status

Sample number	T1	T2	T3	D1	D2	NC
T1	p11	p12	p13	p14	p15	p16
T2	p21	p22	p23	p24	p25	p26
T3	p31	p32	p33	p34	p35	p36
D1	p41	p42	p43	p44	p45	p46
D2	p51	p52	p53	p54	p55	p56
NC	p61	p62	p63	p64	p65	p66

Figure 5: Chaotic matrix

The evaluation indexes are defined as:

1) Accuracy: The proportion of the number of correctly identified samples in the diagnosis process in the number of all samples. The corresponding value of this proportion is higher, indicating that the model has better comprehensive performance.

$$A_{cc} = \frac{\sum_{i=1}^{6} p_{ii}}{\sum_{i=1,j=1}^{6} p_{ij}} \tag{4}$$

2）Precision: Indicates the proportion of samples that are correctly identified as corresponding fault type in the samples that are diagnosed as the fault type.

$$P_{re(i)} = \frac{p_{ii}}{\sum_{j=1}^{6} p_{ji}} \tag{5}$$

3）Recall: Indicates the proportion of samples that are correctly identified as corresponding fault type in the samples that are the fault type.

$$R_{(i)} = \frac{p_{ii}}{\sum_{j=1}^{6} p_{ij}} \tag{6}$$

4）Comprehensive value F1: The harmonic mean of precision and recall.

$$F_{1(i)} = \frac{2 * P_{re(i)} * R_{(i)}}{P_{re(i)} + R_{(i)}} \tag{7}$$

V. EXPERIMENTAL RESULTS AND ANALYSIS

5.1 Characteristic parameters selection

Online monitoring information such as the composition and content of dissolved gas in transformer insulating oil, as well as attribute information such as transformer model and service life are closely related to the operating condition of the transformer, providing an important basis for transformer fault diagnosis. This paper considers 5 attribute information of transformer such as service life, model, rated power, voltage class, load, and 7 gas concentration of CH_4, C_2H_6, C_2H_4, C_2H_2, H_2, CO, CO_2 as characteristic parameters to distinguish the fault type. The coding of the characteristic parameters is shown in Table 1.

Table 1: Characteristic parameters coding

Number	Characteristic Parameters	Number	Characteristic Parameters
0	Service life	6	CH_4
1	Model	7	C_2H_6
2	Rated power	8	C_2H_4
3	Voltage class	9	C_2H_2
4	Load	10	H_2
5	CO_2	11	CO

5.2 Fault status encoding

According to IEC 60599 standard [24], the fault types of transformer mainly include discharge and overheating. The discharge faults are divided into low energy discharge, high energy discharge, and partial discharge. The overheating faults are divided into medium and low temperature overheating and high temperature overheating. In this paper, the normal state and five fault states of transformers are encoded by one-hot, as shown in Table 2.

Table 2: Fault status coding

Coding	Fault types	Fault coding
T1	Low energy discharge	100000
T2	High energy discharge	010000
T3	Partial discharge	001000
D1	Medium and low temperature overheating	000100
D2	High temperature overheating	000010
NC	normality	000001

5.3 Analysis of experimental results

In this paper, we select 400 real transformer fault data from May 2021 to August 2021 of the electric power company in a certain region, among which 300 fault data samples are used as training set and 100 samples are used as test set. The distribution of samples in various states is shown in Table 3.

Table 3: Sample distribution

Operating status	Training set	Test set	Totality
Low energy discharge	55	16	71
High energy discharge	50	18	68
Partial discharge	58	15	73
Medium and low temperature overheating	40	20	60
High temperature overheating	60	19	79
normality	37	12	49
Summation	300	100	400

Adam algorithm is used as the network optimizer of the SqueezeNet-GRU model. The batch size is set to be 20, the weight attenuation rate is set to be 0.0001, and the initial learning rate is set to be 0.002. After 100 epochs training, the final learning rate is 1.8×10^{-5}, the accuracy and loss of the model on the test set are shown in Figure 6. As can be seen from the figure, the error of the model in the first 20 rounds of iterations is high, and the diagnostic accuracy is below 75%. With the increase of the number of iterations, the accuracy of the model is gradually stabilized at about 78%, and the diagnosis error is also gradually decreasing, which indicates that the proposed model can fully extract the characteristics of transformer fault information and detect real operation status of the transformer.

Figure 6: The accuracy and loss curves of the SqueezeNet-GRU model on the test set.

In order to verify the efficiency based on the device portrait and SqueezeNet-GRU model proposed in this article, in the same data set, comparing the model with RNN, GRU, LSTM, CNN-GRU, SVM, and other methods. Meantime, the number of iterations and learning rate are consistent with the model proposed in this paper. Among them, the SVM uses the RBF kernel function, and the penalty coefficient C is set to be 70, and the parameter Gamma is set to be 0.005. The experimental results are shown in Table 4.

Table 4: Test results under different models

Diagnostic model	Precision(%)	Recall(%)	F1(%)
RNN	65	44	52.9
GRU	70	47	55
CNN-GRU	70.7	52.6	57.23
LSTM	69	49.33	56.89
SVM	64.38	43.67	50.98
PSO-BP	71.33	50.24	57.3
SqueezeNet-GRU	78.5	56.12	65.45

Table 5: Accuracy comparison of different methods

Fault type	Test set	GRU		CNN-GRU		SqueezeNet-GRU	
		Mistake number	Accuracy (%)	Mistake number	Accuracy (%)	Mistake number	Accuracy (%)
T1	16	5	69.32	6	68.35	4	75.37
T2	18	6	68.55	6	67.16	4	77.21
T3	15	5	66.74	4	70.98	3	80.09
D1	20	6	70.8	5	71.34	4	78.05
D2	19	6	67.52	6	68.45	4	79.32
NC	12	4	70.01	4	70.9	3	75.46
Summation	100	32	68	31	69	78	74

It can be seen from Table 4 that the diagnostic effect of RNN is poorer than GRU, LSTM, and CNN-GRU. This is because the RNN network structure is complex and the number of parameters is large, resulting in a poor test effect. The diagnosis model based on CNN-GRU has the best results in the above three indicators. This is because it makes full use of the strong spatial feature extraction ability of CNN and the advantages of GRU in extracting time series data. Therefore, the diagnosis effect based on CNN-GRU is obviously better than the other models. On this basis, the diagnosis method based on SqueezeNet-GRU proposed in this paper is tested. It is found that after integrating the lightweight convolutional neural network and GRU, the model can fully extract the transformer fault characteristics, so it is better than the above comparison model in three indexes.

In order to verify the superiority of the proposed method for distinguishing each fault type, the diagnostic accuracy of GRU, CNN, and the proposed method for each fault type are calculated respectively, as shown in Table 5. It can be seen from the table when the GRU is used for fault diagnosis, the diagnostic error rate of D1 is significantly higher, and the six locations are diagnosed as normal and high temperature overheating respectively, indicating that the method is not accurate enough to identify D1. It is easy to confuse with high temperature fault with similar characteristics, and ignore medium and low temperature overheating fault, and the recognition accuracy of normal conditions is not enough. When CNN-GRU is used for fault diagnosis, although the overall accuracy is higher than that of GRU, the recognition ability of T2 type is low, and it cannot meet the requirements of power system production and application. The method proposed in this paper can obviously improve the diagnostic accurate of D1 and T2, and the overall accuracy is the highest among the three methods.

VI. CONCLUSION

Aiming at the problems of low diagnostic accuracy and poor stability caused by the diversity of distribution transformer faults, a new transformer fault diagnosis method based on equipment portrait and improved SqueezeNet-GRU is proposed in this paper. Firstly, the multi-dimensional transformer status portrait is carried out by using genetic optimized spectral clustering. Then the operation state of the transformer is diagnosed by integrating the lightweight network SqueezeNet and Gated Recurrent Unit. The experimental results show that the proposed method can reduce the number of parameters, simplify network structure, greatly shorten the training time, and fully extract the characteristics of time series and spatial structure of transformer fault data. Compared with other fault diagnostic methods, the proposed diagnostic model has higher diagnostic precision, which proves the effectiveness and accuracy of the method proposed in this paper.

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